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Process Chart for Controlling Wafer Defects using Fuzzy Theory

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Abstract

Manufacturers of integrated circuits (IC) frequently utilize c-charts to monitor wafer defects. The clustering of wafer defects increases with the surface area of the wafers. The clustering of defects causes the Poisson-based c-chart to show many false alarms. Although Neyman-based c-chart has been developed to reduce the number of false alarms, it has some shortcomings in practical use. This study presents a process control chart that applies Fuzzy theory and the engineering experience to monitor the clustered defects on a wafer. The proposed method is simpler and more efficient than that of the Neyman-based c-chart. A case study of an IC company in Taiwan demonstrates the effectiveness of the proposed method.

Keywords: Integrated circuits; wafer; defect; statistical process control; defect clustering; Fuzzy theory

1. Introduction

As the information industry grows rapidly, manufacturers of IC are focusing on upgrading their production capabilities in response to strong competition. Therefore, increasing wafer yield is becoming an important issue.

Wafer yield is defined as the percentage of dies that pass the final specification test. The wafer manufacturing process includes hundreds of steps, such as alignment, lithography, etch, deposition, doping and others. In such a complex process, some defects are inevitably produced on the wafer surface, sometimes causing the wafers to be faulty and reducing their yield. Consequently, the number of defects is a significant factor in determining the wafer yield. As IC technology has developed, the surface area of wafers has increased and the clustering of defects has becomes apparent. Hence, like the number of defects on the wafer surface, the clustering of defects affects the wafer yield.

IC manufacturers usually employ c-charts to monitor wafer defects. The use of c-charts assumes wafer defects to be randomly and independently distributed; that is, the number of defects is assumed to follow a Poisson distribution. However, real defect clustering violates this assumption, sometimes causing too many false alarms. Albin and Friedman [1] presented a modified c-chart that is based on a Neyman Type-A distribution to solve this problem. The Neyman-based c-chart widens the control limits and reduces the number false alarms obtained using the Poisson-based c-chart. However, the Neyman-based c-chart can monitor only the variation in the number of defects among wafers, and cannot detect variation in the location of defects within a wafer.

This study applies Fuzzy theory and engineering experience to construct a process control chart that can effectively monitor the clustered wafer defects and defect clustering simultaneously and thus overcome the shortcomings of the Neyman-based c-chart. The proposed method is simpler and more efficient than that of Neyman-based c-charts.

2. Related Work

This section describes a cluster index for measuring the extent of defect clustering, Poisson-based c-chart, Neyman-based c-charts and Fuzzy theory.

2.1 Cluster Index

Stapper [3] indicated that the clustering of defects on a wafer becomes more pronounced as the surface area of the wafer increases. Defect clustering violates the assumption on which the c-chart is based: the defects are not independently or randomly scattered on a wafer. Some cluster indices are developed to measure the extent of the clustering of defects. Of these cluster indices, the cluster index proposed by Jun *et al.* [2], denoted by CI, is proven to be more effective than any others. Moreover, CI does not require any assumptions to be made about the

distribution of defects.

CI is computed as follows. Given that n defects are present on a wafer, and the coordinates of each defect in a two-dimensional plane are given by (X_i, Y_i) for $i=1, 2, \dots, n$, rearrange X_i and Y_i in ascending order to obtain $X_{(i)}$, $Y_{(i)}$, where $X_{(i)}$ represents the x coordinate of the i th defect, and $Y_{(i)}$ is the y coordinate of the i th defect. Hence, the intervals V_i and W_i

$$V_i = X_{(i)} - X_{(i-1)}, i = 1, 2, \dots, n$$

$$W_i = Y_{(i)} - Y_{(i-1)}, i = 1, 2, \dots, n$$

where $X_{(0)}$ and $Y_{(0)}$ are set to zero.

CI can now be expressed as follows.

$$CI = \min \left\{ (\text{coefficient of variation of } V_i)^2, (\text{coefficient of variation of } W_i)^2 \right\}$$

The mean and variance of V_i can be written as \bar{V} and S_v^2 , respectively. The mean and variance of W_i can be written as \bar{W} and S_w^2 , respectively. Then, the CI can be expressed as follows.

$$CI = \min \left\{ \frac{S_v^2}{\bar{V}^2}, \frac{S_w^2}{\bar{W}^2} \right\}.$$

When the defects are uniformly distributed, the CI index equals one. If CI exceeds one, the defects are clustered. A larger CI corresponds to more severe clustering.

2.2 Poisson-based c-chart

In IC manufacturing, the number of defects is the quality characteristic on which the conventional c-chart is typically based. The number of defects used to construct the c-chart must be Poisson-distributed, and so have a probability distribution function given by,

$$p(N = n) = \frac{e^{-\mu} \mu^n}{n!},$$

where n represents the number of defects on the surface

and μ represents the average number of defects on a wafer.

According to the properties of Poisson distribution, the upper control limit (UCL) of the c-chart can be obtained as follows.

$$UCL = \mu + 3(\mu)^{\frac{1}{2}}.$$

Recently, as the surface area of wafers has increased from 4 inches to 12 inches, the clustering of wafer defects has becomes more apparent, such that using the c-chart to monitor the number of defects produces many false alarms.

2.3 Neyman-based c-chart

A modified c-chart based on Neyman Type-A distribution was developed to reduce the number of false alarms. The Neyman Type-A distribution is a member of family of compound Poisson distributions. Albin and Friedman [1] proposed a Neyman-based c-chart that improved on the Poisson-based c-chart. The Neyman Type-A distribution assumed that the number of defect clusters follows a Poisson distribution with mean λ , and that the number of defects in each cluster is also Poisson-distributed with mean ϕ . The probability distribution function of a Neyman Type-A distribution is as follows.

$$P_n(\lambda, \phi) = P_r(N = n) = \sum_{j=1}^{\infty} e^{-\lambda} \frac{\lambda^j}{j!} e^{-j\phi} \frac{(j\phi)^n}{n!},$$

where n represents the number of defects on a wafer's surface; λ represents the average number of defects on a wafer, and ϕ represents the average number of defects per cluster.

The expected value and variance of Neyman Type-A distribution are given as follows.

$$E(x) = \lambda\phi, \quad V(x) = \lambda\phi(1 + \phi).$$

The ratio of $V(x)$ to $E(x)$ is $(1+\phi)$, so the Neyman-based c-chart widens the control limits on the Poisson-based c-chart and can therefore effectively reduce the number of false alarms that would otherwise be determined by the Poisson-based c-chart. However, the method proposed by Albin and Friedman still has some shortcomings. They considered the number of defects on a wafer as the quality characteristic, on which to determine the control limits of the Neyman-based c-chart. Their method monitors only the variability of defects among wafers. The variability of the number of defects within a wafer cannot be detected.

2.4 Fuzzy Theory

Zadeh [5] first developed Fuzzy theory, which is utilized to deal with Fuzzy events. This section briefly reviews Fuzzy theory.

2.4.1 Fuzzy Set

Fuzzy theory is based on Fuzzy sets. The characteristic function of a crisp set is defined to be either zero or one, and the relationship of the characteristic function to a Fuzzy set is determined with reference to a dichotomy. However, the concept of dichotomy here differs from that typically used. The human language includes many vague words. Therefore, Zadeh used a membership function to represent the intensity: with which one element belongs to one set; a stronger intensity corresponds to a membership function closer to one; a weaker intensity corresponds to a function closer to zero.

2.4.2 Fuzzy logics and Fuzzy inference

A Fuzzy proposition has two forms; one is the atomic Fuzzy proposition and the other is compound Fuzzy proposition. Fuzzy logic is defined as follows.

1. If a compound Fuzzy proposition uses “and” to combine two atomic Fuzzy propositions, such as ‘X is A’ and ‘y is B’, then the membership function can be defined as $\mu_R(x, y) = \min(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y))$, $(x, y) \in X \times Y$.
2. If a compound Fuzzy proposition uses “or” to combine two atomic Fuzzy propositions, such as ‘X is A’ or ‘y is B’, then the membership function is $\mu_R(x, y) = \max(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(y))$, $(x, y) \in X \times Y$.
3. If a compound Fuzzy proposition uses “implies” to combine two atomic Fuzzy propositions, such as ‘X is A’ implies ‘y is B’, then the membership function is $\mu_R(x) = \min(1, 1 - \mu_{\tilde{A}}(x) + \mu_{\tilde{B}}(y))$, $(x, y) \in X \times Y$.

Fuzzy inference is similar to inference in binary logic. The difference between these two inferences is that a Fuzzy inference involves contiguous sets, unlike in binary logics, wherein sets are defined absolutely and as opposing each other. A Fuzzy inference includes Fuzzy steps; many Fuzzy steps are combined in a computable system. Some value is imagined to be input into this system. Figure 1 depicts the process of Fuzzy inference.

Fuzzy inference provides a different method of control from the traditional method. A Fuzzy inference system includes experts’ knowledge, operators’ experience, the membership function and the development of rules; therefore, the Fuzzy inference system is essentially intelligent.

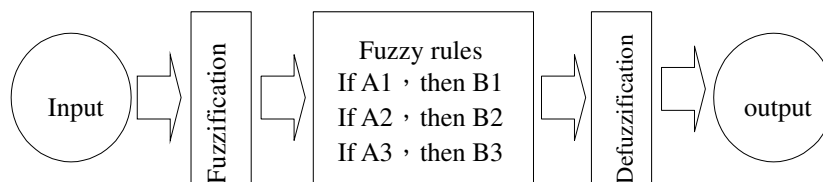


Figure 1. The process of Fuzzy inference

3. Proposed Procedure

This study develops an efficient method for monitoring the clustered defects. Fuzzy theory is utilized to construct a control chart to monitor simultaneously the number of defects across various wafers and defect clustering. The proposed procedure is described as follows.

Step 1: Obtain the wafer map using the KLA 2110 wafer inspection system.

The KLA 2110 wafer inspection system can provide in-line wafer inspection information, including the number of defects, their sizes, their locations and their types.

Step 2: Determine the number of defects and compute CI.

Step 3: Construct the membership functions that correspond to the number of defects, CI and output of the process.

Both the number of defects and clustering are important characteristics that might affect wafer yield. This study therefore considers these two quality characteristics as the input variables of the Fuzzy inference system and the output of the process as the output of Fuzzy inference system. The number of defects can be classified using seven levels – very-low, low, medium-low, medium, medium-high, high, very-high (see Fig.2), and the membership function of each Fuzzy set is constructed accordingly.

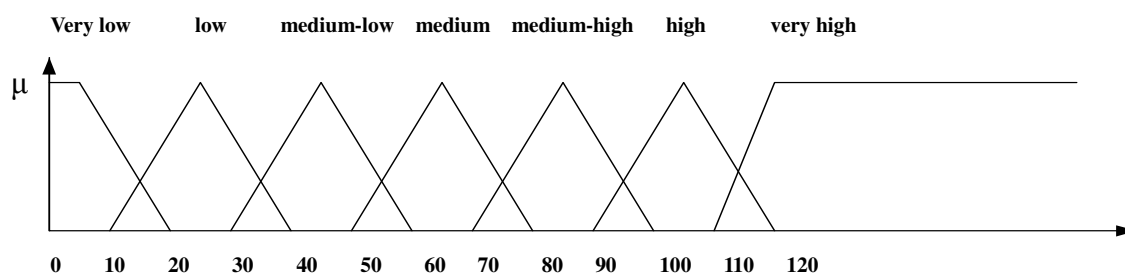


Figure 2. Seven levels of numbers of defects

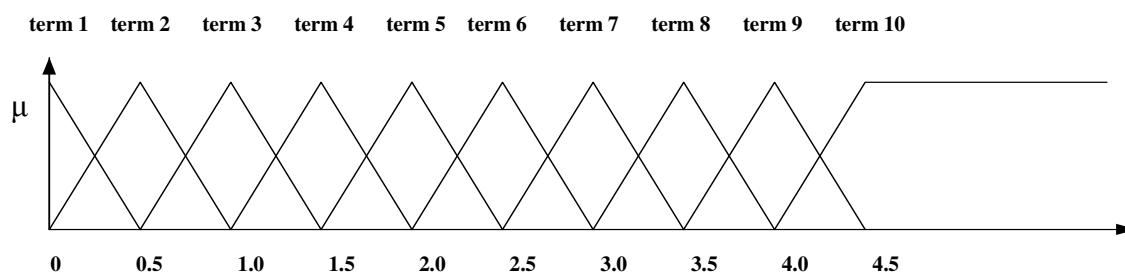


Figure 3. Ten statements about clustering phenomena

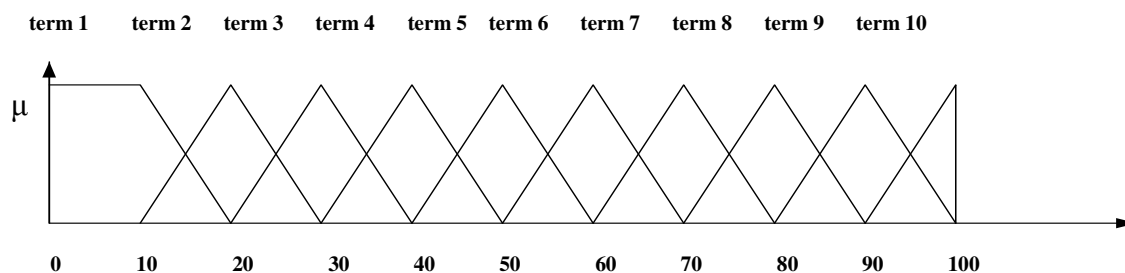


Figure 4. Ten output levels

Clustering phenomena can be classified using ten statements, term 1 to term 10 (Fig. 3), and the membership function of each Fuzzy set is constructed accordingly.

The output can be classified into ten levels, represented by terms 1 to 10 (Fig. 4), respectively, the membership function of each Fuzzy set is constructed accordingly.

Step 4: Establish a warehouse of rules.

When many defects are present, without clustering, the process is considered to be out of control; when a few defects are present but clustering is significant, the process is said to be under control; the corresponding rules generated to monitor the process can be expressed as follows.

R_1 : IF Defect is very high AND CI is term 1, THEN Value is term 10

R_2 : IF Defect is very high AND CI is term 2, THEN Value is term 10

.

R_i : IF Defect is medium AND CI is term 10, THEN Value is term 2

.

R_{70} : IF Defect is very low AND CI is term 10, THEN Value is term 1

Step 5: Make Fuzzy inference

In the system for controlling the manufacturing of wafers, (established using Fuzzy theory, the number of defects and the CI value are determined. For example, if a wafer is detected; the number of defects is 93, and the CI value is 0.866, then an input, (93, 0.866), is generated; this input activates four rules, as follows.

R : IF Defect is medium-high AND CI is term 2 , THEN Value is term 10

R : IF Defect is medium-high AND CI is term 3 , THEN Value is term 9

R : IF Defect is high AND CI is term 2 , THEN Value is term 9

R : IF Defect is high AND CI is term 3 , THEN Value is term 9

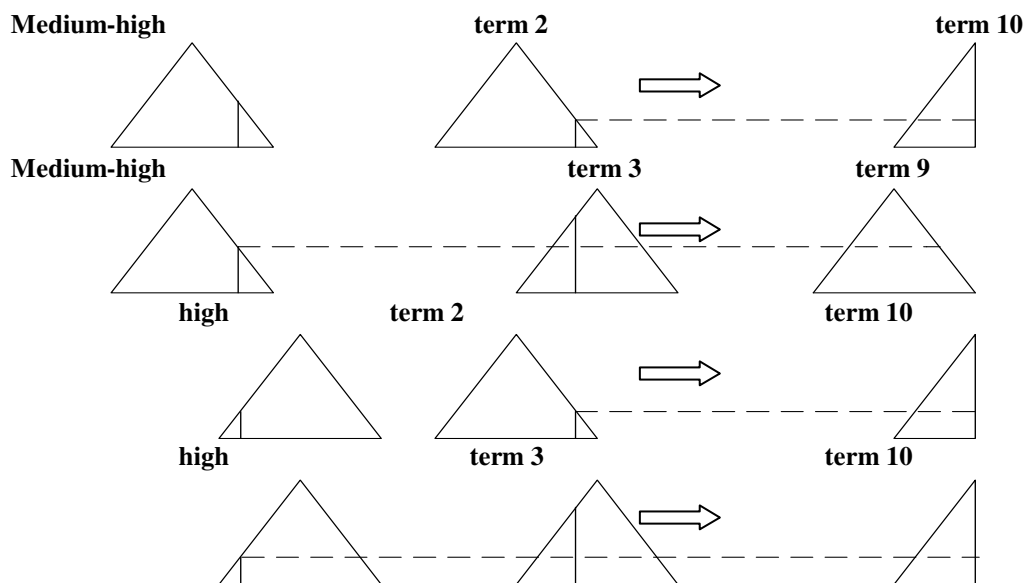


Figure 5. Fuzzy inference rules

Fig. 5 presents these four rules.

A new Fuzzy set can be obtained by utilizing Fuzzy set from the four rules, as shown in Fig. 6

Step 6: Draw the Fuzzy control chart and construct the control limits.

After the defect data are collected, the defect data are transformed into output of the Fuzzy inference rules using the six steps described above. Hence, a moving range ($\bar{X}-R_m$) control chart can be constructed to monitor simultaneously the number of defects and clustering. If all of the data plotted on the chart fall within the control limits, then these control limits can be regarded as the limits of the process control chart; if one or two points lie outside of the control limits, then the causes must be found and corrected.

Step 7: Establish rules for determining that the process is out of control.

Consider Fig. 7, for example. If a point falls inside the control limits, then the process is said to be under control.

If points fall outside the control limits, then the process is said to be out of control. With reference to Fig. 7, suppose points 1 and 2 are out of control and fall beyond the upper control limit; then, the process's being out of control is caused by an excess of defects; assume that points 3, 4 and 5 are out of control and fall below the lower control limit; then, defect clustering is determined to have made the wafer manufacturing process unstable.

4. Conclusion

The clustering of wafer defects increases with the surface area of wafers. The clustering of wafer defects not only impacts the yield of the IC production line, but also causes the Poisson-based c-chart to fail to monitor the wafer process effectively. Albin and Friedman [1] developed the Neyman-based c-chart as an improvement on the Poisson-based c-chart. The Neyman c-chart widens the control limits of the Poisson-based c-chart and reduces the number of false alarms. However, that Neyman c-chart cannot detect the clustering defects between wafers.

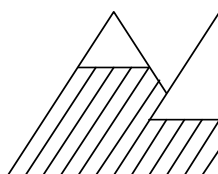


Figure 6. Union chart

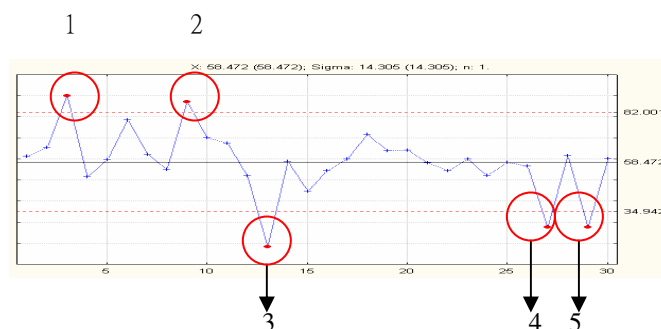


Figure 7. A $\bar{X}-R_m$ control chart for monitoring simultaneously the number of defects and clustering

The contributions of the proposed method can be summarized as follows.

1. The Fuzzy system incorporates the knowledge of experts and the experience of engineers, and can therefore effectively monitor simultaneously the number of defects and the extent of clustering. The proposed Fuzzy control chart can also reduce the workload associated with constructing two separate process control charts to monitor the number of defects and clustering.
2. Engineers with little knowledge of Statistics can apply the proposed Fuzzy control chart easily. This chart is very helpful in judging real process conditions.
3. The proposed control chart is simpler and more efficient than both the Poisson-based c-chart and the Neyman-based c-chart.

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